Chapter Four FINDINGS AND EVALUATION

4. Findings and Evaluation

4.1. Descriptive Statistics

As illustrated in Table 8., majority of the respondents were females (76.6%), while males accounted for about 20% of the responses. In terms of age, most of the participants were younger millennials aged 25 – 29 (41.1%), followed closely by Gen Zs aged 18 – 24 (39.1%), and core millennials aged 30 -34 (19.5%). Although these figures do not confirm to the UAE's actual gender distribution (70% males, 30% females), they do align with the country's age group distribution with more millennial respondents than Gen Zs (Global Data, 2020). Such demographic discrepancies were also observed in previous cross sectional studies (Antwi, 2021; De Canio, Fuentes-Blasco and Martinelli, 2021). The sample largely comprised of employed individuals (75.0%), but also included few students (19.5%) and miscellaneous occupations (5.5%), thereby making it more representative of the target population (Bryman and Bell, 2011).

Table 8: Sample's demographic and app behaviour distribution.

Variables	Categories	Frequency	Percentage
Gender	Male	25	19.5%
	Female	98	76.6%
	Preferred not to disclose	5	3.9%
Age	18-24	50	39.1%
	25-29	53	41.1%
	30-34	25	19.5%
Occupation	Student	25	19.5%
	Employed (Private sector/ Public Sector/ Self Employed)	96	75.0%
	Others (Family Manager/ Unemployed/ Prefer not to disclose)	7	5.5%
App Used	Namshi	76	59.4%
	Noon Fashion	32	25.0%
	6th Street	14	10.9%
	Sivvi	4	3.1%
	Styli	2	1.6%
Usage Location	At home	104	81.3%
	At work	12	9.4%
	On the commute	9	2.3%
	At place of study	3	7.0%
Usage Frequency	At least once a week	37	28.9%
	At least once a month	46	35.9%
	At least once in three months	24	18.8%
	At least once in six months	14	10.9%

At least once a year	3	2.3%
At least once in two years	4	3.1%

Namshi emerged as the most commonly used pureplay fashion app in the region (59.4%), followed by Noon (25.0%). Since Noon also retails other categories such as electronics and household items, compared to Namshi which specializes only in fashion and apparel, Noon may have outranked Namshi in other market analysis as their methodology was not limited to fashion categories (Euromonitor, 2021a). However, the results of this study indicate that Namshi has a potentially higher preference than Noon amongst consumers shopping solely for fashion. As expected from literature, 6th street was third in place (Euromonitor, 2021a). Most consumers used the app to purchase products (73.3%), browse for new trends (64.2%), and be up to date with discounts/ offers (46.7%), partly concurring with Mclean *et al*. (2019).

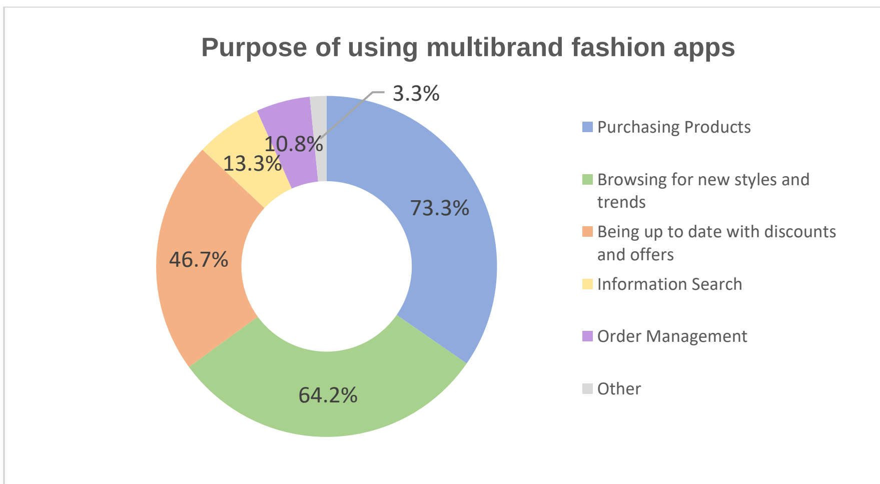

Figure 3:Pupose of using multibrand fashion apps.

Crosstabs were used to analyze the effects of gender and age on app usage location and frequency. Collectively about 81% of respondents usually accessed the app at home, largely diverging from McLean et al.'s (2019) study wherein most respondents used m-commerce apps while commuting, possibly due to geographic/ cultural differences in both samples. More males (32%) were potentially likely to use the app outside home than females (16.3%). While Millennials mostly used the app at home, over a quarter of Gen Zs were likely to be using the app outside of home. Close to two-thirds of the sample shopped using a pureplay fashion app at least once a month. Males seemed to be on fashion apps more frequently than females with 76% using an app at least once a month, compared to about 62.2% females. In terms of age, more Millennials (67%) were likely to use the app at least once a month than Gen Zs (62%). Following figures visually summarize the information captured by crosstabs. The detailed cross tabulations are reported in section 4.4.

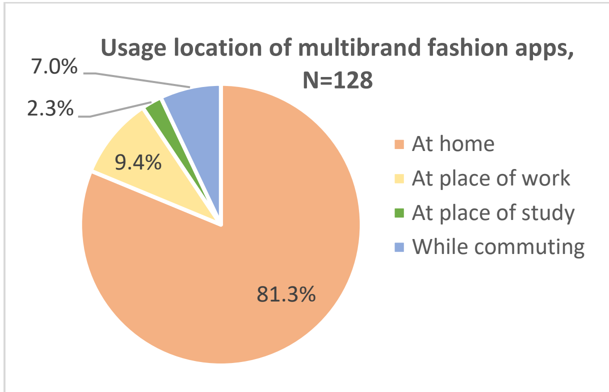

Figure 4: App usage location of multibrand fashion apps.

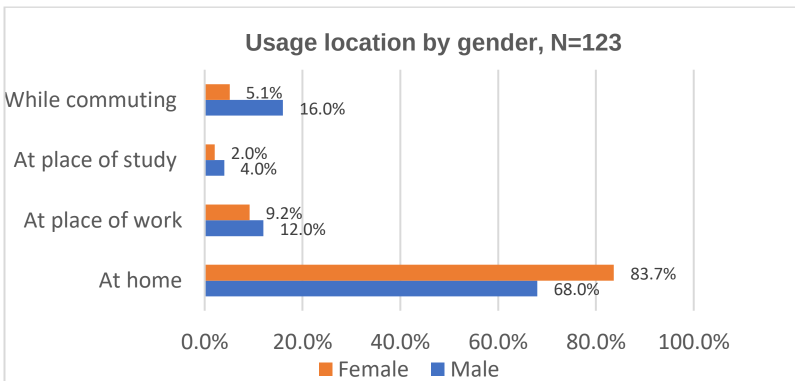

Figure 5: App usage location by gender.

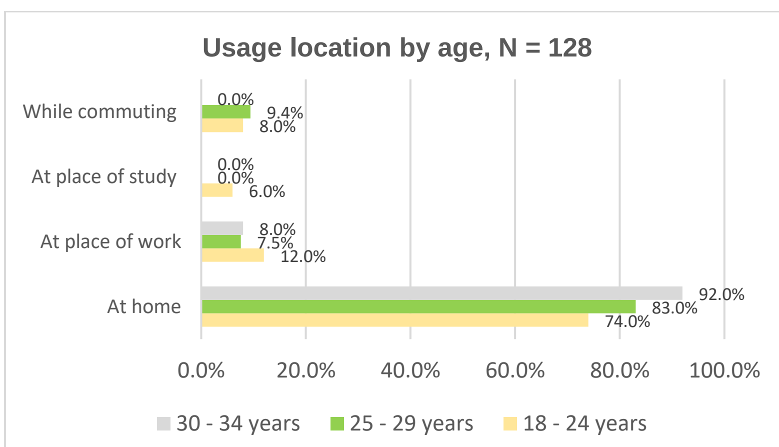

Figure 6: App usage location by age.

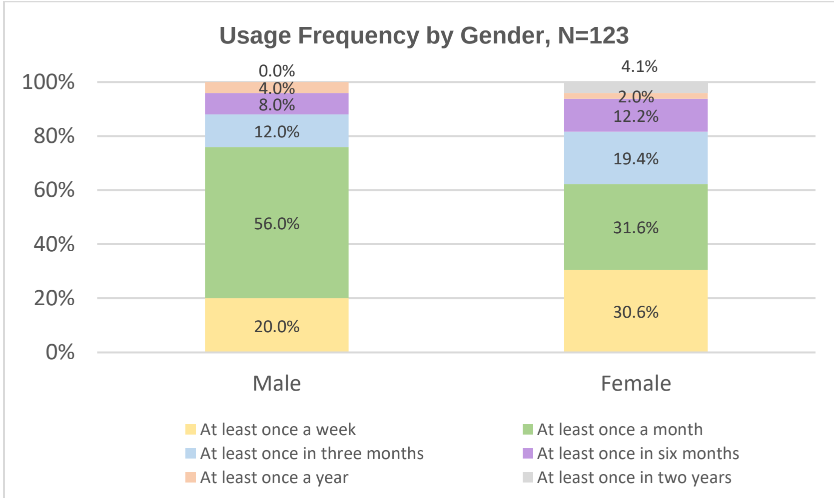

Figure 7: App usage frequency by gender.

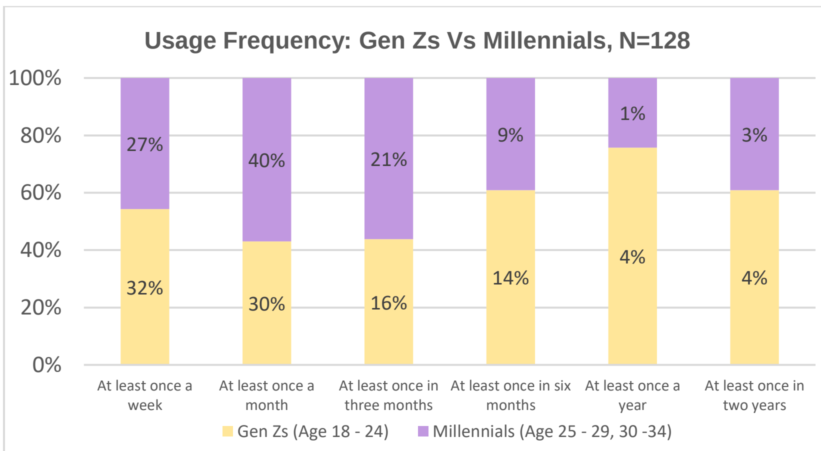

Figure 8: App usage frequency - Gen Zs Vs. Millennials.

As illustrated in Table 9., on an average most respondents were likely to have found their user experience to be transparent, convenient (ubiquitous), and pleasurable as indicated by the higher mean scores for TUX, UBQ and PLE compared to other constructs. Scores for PLE, ARO, and RPI had the highest standard deviations signaling that respondents may have largely differed on their attitudes regarding these constructs. The exact frequencies obtained for each construct have been reported in Appendix 3 – A 3.6.

Table 9: Descriptive statistics obtained for mean scores of all Variables used in hypotheses development.

Construct	Mean	Median	Mode	Std. Deviation	Minimum	Maximum
NoA	3.805	4.000	4.000	0.553	2.333	5.000
PER	3.440	3.333	4.000	0.665	1.667	5.000
TUX	4.225	4.000	4.000	0.588	2.500	5.000
UBQ	4.284	4.000	4.000	0.552	2.667	5.000
AFS	3.680	3.667	4.000	0.802	1.667	5.000
PLE	3.932	4.000	4.000	0.748	1.667	5.000
ARO	3.344	3.333	3.000	0.880	1.000	5.000
DOM	3.786	4.000	4.000	0.572	2.000	5.000
RPI	3.301	3.500	4.000	0.791	1.750	5.000

4.2. Preliminary Analysis

4.2.1. Normality

PLS SEM is based on the principles of non-parametric statistical analysis and therefore does not require the assumption of normality as other multivariate analysis do (Hair *et al.*, 2014). However, largely non-normal data may contribute towards incorrect assessment of the significance levels (Hair *et al.*, 2014). Thus, all the nine constructs were subjected to normality tests using SPSS V 27.

Normality results for the dependent variable, repurchase intentions (RPI) are illustrated below (normality of other variables is reported in Appendix 3 – A 3.7 and 3.8). As evident, RPI and all the other constructs were relatively normally distributed with reasonably straight normal Q-Q plots and most points collected around the zero line in detrended normal Q-Q plots (Pallant, 2016). Skewness and Kurtosis were within acceptable +1 and -1 range (Hair *et al.*, 2014; Pallant, 2016). Mean and 5% trimmed mean values were close, indicating an acceptable normal spread (Hair et al., 2014; Pallant, 2016). Although Kolmogorov-Smirnov and Shapiro-Wilk statistic were significant ($p < 0.05$), indicating violation of normality, such results are usually observed in larger samples (Clow and James, 2014; Pallant, 2016). Also, by Central Limit theorem, N>30, indicating data is normally distributed (Saunders *et al.*, 2019).

Table 10:Normality descriptives for RPI. Mean and 5% Trimmed Mean values are almost equal,

Construct	**Mean** Statistic Std. Error	**95% C.I for Mean** Lower Bound Upper Bound	**5% Trimmed Mean**	**Skewness** Statistic Std. Error	**Kurtosis** Statistic Std. Error
RPI	3.300 0.069	3.162 3.439	3.295	-0.074 0.214	-0.681 0.425

indicating RPI data is normally distributed. Skewness and Kurtosis are within acceptable -1 and +1 limits for normality.

Table 11: Kolmogorov-Smirnov and Shapiro-Wilk's test for normality of RPI scores. Tested at $p < 0.05$ significance level. Although Kolmogorov-Smirnov and Shapiro-Wilk statistic are significant ($p < 0.05$), indicating violation of normality, such results are usually observed in larger samples.

Tests of Normality						
	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
Constructs	Statistic	df	Sig.	Statistic	df	Sig.
RPI	0.107	128	0.001	0.967	128	0.003
a. Lilliefors Significance Correction						

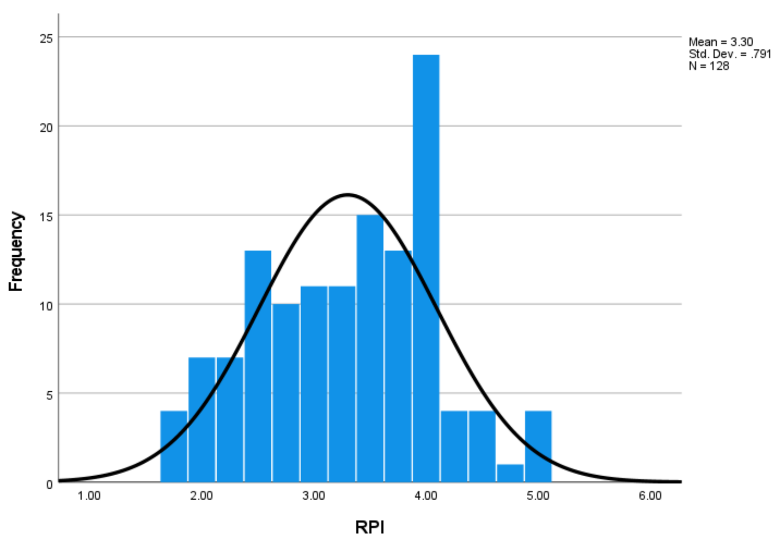

Figure 9: Histogram plot with normality curve for RPI scores.

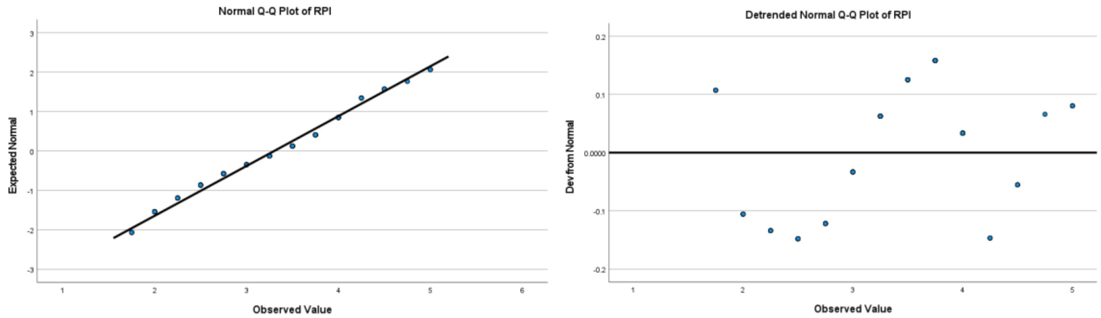

Figure 10: Normal Q-Q Plot and Detrended Normal Q-Q Plot of RPI.

4.2.2. Screening for Outliers

A total of 18 outliers were detected using box plots generated in the normality analysis. The outliers belonged to three constructs – NoA, PLE, and DOM. The mean and 5% trimmed mean values of the respective constructs were cautiously investigated and found to be approximately equal (see Appendix 3 – A 3.7.) , thereby permitting the retention of these data points in order to maintain an appropriate sample size for further analysis (Pallant, 2016).

Figure 11. displays the box plot for Repurchase Intentions as an example. The remaining box plots have been illustrated in Appendix 3 – A 3.8.

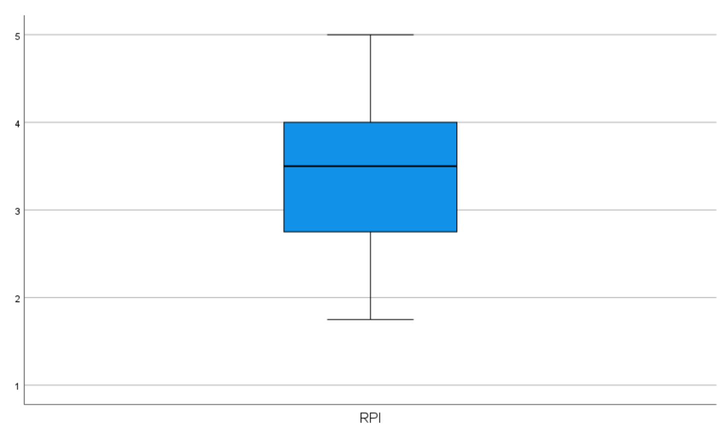

Figure 11: Box plot for RPI indicating absence of outliers.

4.2.3. CMB (Harman's one-factor test)

The measurement method used for this study may have induced CMB from various sources such as acquiescence, halo effect, respondent's social desirability, leniency effects, etc. (Podsakoff *et al.*, 2003). In the reviewed literature, researchers have assessed CMB using either of three statistical remedies – Harman's one-factor test (Hsu and Chen, 2018), Common method variance (Hsieh, Lee and Tseng, 2021), or Full collinearity based approach (Lim *et al.*, 2021). For the purpose of this study, CMB was tested using Harman's one-factor test by loading all items in an Exploratory Factor Analysis (EFA) with unrotated first factor. The total variance explained by the first factor was 26.6%, i.e. < 50%, confirming CMB was not a problem (see Appendix 3 – A 3.9.) (Podsakoff et al., 2003; Hsu and Chen, 2018).

4.2.4. KMO and Bartlett's test of sphericity

The KMO statistic was > 0.5 and Bartlett's test of sphericity was significant ($p < 0.001$), indicating that the variances in the variables were caused by underlying factors. Thus, the sample was adequate for factor analysis (Hsu and Chen, 2018; Ali and Bhasin, 2019). (Note: factor analysis was replaced with its PLS SEM equivalent - measurement model analysis, discussed in section 4.3).

Table 12: KMO and Bartlett's test of sphericity.

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		**.771**
Bartlett's Test of Sphericity	Approx. Chi-Square	313.926
	df	36
	Sig.	**<.001**

4.3. Hypotheses Testing: PLS SEM

There are two ways to perform Structural Equation Modeling (SEM) for estimating relationships between variables – CB SEM (Covariance based approach), and PLS SEM (Partial Least Squares approach) (Hair *et al.*, 2010). Following the procedure adopted in extant literature, the paths hypothesized in this study were investigated using the PLS approach (Hsu and Chen, 2018; De Canio, Fuentes-Blasco and Martinelli, 2021; Hsieh, Lee and Tseng, 2021). The reason being, PLS provides greater statistical power when dealing with complex models and relatively low samples sizes compared to its covariance-based equivalent (Hair *et al.*, 2014). Although CB-SEM is suitable for theory confirmation, PLS offers explanatory/ verification modelling and flexibility with sample distributions (Hsu and Chen, 2018; Hsieh, Lee and Tseng, 2021). In addition, akin to multiple regression, PLS also provides stronger predictive capabilities based on OLS regressions to explain the model's 'partial regression relationships' (Hair *et al.*, 2014).

SEM was conducted in two stages using Smart PLS based on guidelines prescribed by (Hair *et al.*, 2014) :

i. **Outer Model aka Measurement Model assessment** – Involves empirical validation of the relationship between constructs and their respective indicators (scale items), by examining reliability and validity of the measures.
ii. **Inner Model aka Structural Model assessment** – Involves empirical validation of the relationships between various constructs (variables), i.e., the hypotheses and structural model.

4.3.1. Measurement Model (Outer Model)

Measurement model was evaluated using the foundations of principal component-based estimation in order to ascertain reliability and validity (De Canio, Fuentes-Blasco and Martinelli, 2021). The outer model comprised of three to four reflective indicators (arrows emerging out from the construct) for each of the nine variables. Internal consistency reliability was achieved since all CR values were greater than 0.7 (Hair *et al.*, 2014; Hsieh, Lee and Tseng, 2021). Cronbach's α was slightly below the 0.7 requirement for NoA, DOM, and PER. However, as prescribed by Hair *et et. al* (2014), Cronbach's α is a conservative measure of reliability and should be used only secondary to CR which was already well above the threshold for all constructs. Convergent validity was established since all AVE values were > 0.5 (Hair *et al.*, 2014; Hsu and Chen, 2018).

As discussed in chapter 3 (Table 7.), almost all factor loadings were acceptable (> 0.7) (Hair *et al.*, 2014; Hsu and Chen, 2018). PER_1 was deleted despite having a factor loading above 0.7 since it plummeted the AVE to below 0.5, whereas NoA_1 and PER_4 were retained despite having loadings slightly less than 0.7, as their removal did not lead to a decrease in AVE below threshold (Hair *et al.*, 2014).

Discriminant validity was ascertained using the Fornell-Larcker Criterion and HTMT ratios. Square roots of all AVE values (i.e., the diagonal values in Table 14.) in the correlation matrix were greater than the construct's correlation with any other construct, and all HTMT ratios (see Table 15.) were lesser than 0.85 or 0.90, thereby confirming discriminant validity (Fornell and Larcker, 1981; Hsu and Chen, 2018).

Table 13: Composite Reliability (CR)< Cronbach's α and convergent validity (AVE). Cronbach's α > 0.6 retained since all CR > 0.7 and all AVE > 0.5 (Hair et al.*, 2014)*

Construct	CR	Cronbach's α	AVE
AFS	0.936	0.900	0.831
ARO	0.848	0.733	0.652
DOM	0.809	0.648	0.586
NoA	0.808	0.640	0.588
PER	0.813	0.665	0.597
PLE	0.869	0.774	0.688
RPI	0.917	0.879	0.733
TUX	0.902	0.857	0.698
UBQ	0.900	0.834	0.749

Table 14: Discriminant validity. Fornell-Larcker Criterion: Square root of AVE of a construct (i.e., the diagonal values in bold) should be greater than the construct's correlation with any other construct.

Construct	AFS	ARO	DOM	NoA	PER	PLE	RPI	TUX	UBQ
AFS	**0.911**								
ARO	0.090	**0.807**							
DOM	0.324	0.304	**0.765**						
NoA	0.148	0.403	0.308	**0.767**					
PER	-0.050	0.228	0.347	0.196	**0.773**				
PLE	0.247	0.509	0.410	0.315	0.276	**0.830**			
RPI	0.334	0.380	0.367	0.369	0.260	0.380	**0.856**		
TUX	0.553	0.220	0.446	0.286	0.138	0.383	0.193	**0.835**	
UBQ	0.454	0.170	0.348	0.321	0.047	0.326	0.196	0.615	**0.866**

Table 15: Discriminant validity evaluation using Heterotrait-Monotrait (HTMT) ratio. (should be less than 0.85 or 0.90) (Hair et al.*, 2014).*

Construct	AFS	ARO	DOM	NoA	PER	PLE	RPI	TUX	UBQ
AFS									
ARO	0.101								
DOM	0.424	0.431							
NoA	0.215	0.581	0.473						
PER	0.158	0.305	0.507	0.300					
PLE	0.282	0.682	0.580	0.459	0.372				
RPI	0.383	0.451	0.478	0.500	0.324	0.460			
TUX	0.617	0.285	0.583	0.398	0.190	0.460	0.221		
UBQ	0.527	0.225	0.457	0.430	0.079	0.396	0.223	0.729	

4.3.2. Structural Model (Inner Model) – Hypotheses Testing

The structural model was examined to evaluate the hypothesized relationships between constructs and the model's predictive capabilities, in order to conclude whether the theory could be confirmed empirically. Following steps were adopted in the assessment of the structural model:

i. Multicollinearity was examined to rule out its impact on the estimation of weights and significance levels. Variance Inflation Factor, i.e., VIF was below 5, and Tolerance was above 0.20 (see Table 19.). Thus, no threat of multicollinearity was observed, confirming data was suitable for SEM analysis (McLean *et al.*, 2019; Hsieh, Lee and Tseng, 2021; Lim *et al.*, 2021).

ii. The structural model was assessed using significance of paths (β, aka path coefficient), coefficient of determination (R^2), and predictive relevance (Q^2). 5000 resamples were generated at a 95% significance level (two-tailed) using the Bootstrapping function on Smart PLS to determine β and R^2 (Hair *et al.*, 2014). Blindfolding analysis was performed to investigate Q^2.

    R^2 values ranging from 0 to 1 are indicative of a model's increasing predictive power as they explain the variance in the endogenous variables (arrows going into the variable) brought about by the exogeneous/ independent variables. R^2 values for ARO, DOM, and RPI were above 0.1 indicating acceptable predictive capability, whereas PLE had a relatively low explanatory power (<0.1) , possibly due to the use of a single predictor (AFS) (Hair *et al.*, 2014; Hsieh, Lee and Tseng, 2021).

Q^2 values obtained for all endogenous constructs (ARO, DOM, PLE, and RPI) were above 0, confirming that the model has predictive relevance (Hair *et al.*, 2014; Hsu and Chen, 2018).

iii. Next, the hypotheses were tested to ascertain the significance of the relationships between constructs, based on threshold values of the T-statistic ($t>1.96$) and p value ($p < 0.05$) (Hair *et al.*, 2014; Lim *et al.*, 2021).

Newness of Assortment has significant positive influence on Arousal (H1: $\beta = 0.373$, $t = 4.378$, $p < 0.05$), whereas Personalization has an insignificant positive effect on Arousal (H2: $\beta = 0.155$, $t = 1.822$, $p = 0.069$).

Transparent User Experience is positively and significantly associated with feelings of Dominance (H3: $\beta = 0.376$, $t = 4.055$, $p < 0.05$), whereas Ubiquity has a small positive but insignificant effect on Dominance (H4: $\beta = 0.112$, $t = 1.167$, $p = 0.243$).

After-Sales Service has a significant positive relation with state of Pleasure (H5: $\beta = 0.247$, $t = 3.025$, $p < 0.05$).

Repurchase Intentions were significantly positively influenced by feelings of Arousal (H6a: $\beta = 0.222$, $t = 2.159$, $p < 0.05$) and Dominance (H6b: $\beta = 0.234$, $t = 2.421$, $p < 0.05$), but insignificantly by Pleasure (H6c: $\beta = 0.171$, $t = 1.528$, $p = 0.127$).

iv. Effect size, f^2 was determined to examine a predictor's contribution to the R^2 value of corresponding endogenous construct. Drawing on Cohen's (1992) guidelines, NoA ($f^2 = 0.163$) and PER ($f^2 = 0.028$) had a medium and small effect on ARO respectively. TUX ($f^2 = 0.106$) and UBQ ($f^2 = 0.010$) had a medium and small effect on DOM respectively. ARO ($f^2 = 0.046$), DOM ($f^2 = 0.060$), and PLE ($f^2 = 0.025$) had small, small to medium, and small effects on RPI respectively (Lim *et al.*, 2021). Effect size of AFS on PLE was not estimated since the f^2 estimation requires minimum two predictors for a given construct. f^2 values were calculated using the below equation, where $R^2_{included}$ and $R^2_{excluded}$ refer to the R^2 values of an endogenous variable when a particular predictor is retained or dropped from the estimation the model (Cohen, 1992; Hair *et al.*, 2014).

Equation 1: Effect size calculation.

$$f^2 = \frac{R^2_{included} - R^2_{exluded}}{1 - R^2_{included}}$$

Model fit was assessed using SRMR (Standardized Root Mean Residuals) which was 0.080, i.e., below the threshold of 0.1, indicating that the data fits the model (Hsu and Chen, 2018).

Table 16. summarizes the results of the hypotheses discussed above.

It is important to note that although this study comprised of three intermediary variables (pleasure, arousal and dominance), it did not specifically hypothesize any mediating relationships in its objectives. This was similar to the approach adopted by Hsieh, Lee and Tseng (2021). The reason being, investigation of mediating effects would require the creation of additional paths from the five exogenous constructs (AMCs) towards repurchase intentions, thereby altering the predictive power (R^2) induced by the three intermediaries – pleasure, arousal, and dominance on repurchase intentions (Hair *et al.*, 2014). This would result in an alternate competing model which was beyond the scope of the present study.

Table 16: Summary of results obtained from hypotheses testing.

Path	Conclusion	β	STDEV	T Statistic	P Values
H1: NoA --(+)--> ARO, Newness of assortment is positively associated with feelings of arousal.	**Supported**	0.373	0.085	**4.378**	**0.000**
H2: PER --(+)--> ARO, Personalization is positively associated with feelings of arousal.	Not Supported	0.155	0.085	1.822	0.069
H3: TUX --(+)--> DOM Transparent user experience is positively associated with feelings of dominance.	**Supported**	0.376	0.093	**4.055**	**0.000**
H4: UBQ --(+)--> DOM, Ubiquity is positively associated with feelings of dominance.	Not Supported	0.112	0.096	1.167	0.243

H5: AFS --(+)--> PLE After-sales services are positively associated with feelings of pleasure.	**Supported**	0.247	0.082	**3.025**	**0.002**
H6a: ARO --(+)--> RPI Feelings of arousal have a positive influence on repurchase intentions.	**Supported**	0.222	0.103	**2.159**	**0.031**
H6b: DOM --(+)--> RPI Feelings of dominance have a positive influence on repurchase intentions.	**Supported**	0.234	0.097	**2.421**	**0.015**
H6c: PLE --(+)--> RPI Feelings of pleasure have a positive influence on repurchase intentions.	Not Supported	0.171	0.112	1.528	0.127

Table 17: R^2 and Q^2 values of endogenous constructs.

Endogenous Construct	R^2	Q^2
ARO	0.186	0.104
DOM	0.205	0.110
PLE	0.061	0.036
RPI	0.237	0.160

Table 18: Effect size, f^2, of various exogenous variables on corresponding endogenous constructs.

Predictor	Endogenous Construct	R^2 included	R^2 excluded	f^2
NoA	ARO	0.186	0.053	0.163
PER	ARO	0.186	0.163	0.028
TUX	DOM	0.205	0.121	0.106
UBQ	DOM	0.205	0.197	0.010
ARO	RPI	0.237	0.202	0.046
DOM	RPI	0.237	0.191	0.060
PLE	RPI	0.237	0.218	0.025

Table 19: VIF (< 5) and Tolerance values (> 0.20). Tolerance values are reported in brackets.

Construct	AFS	ARO	DOM	NoA	PER	PLE	RPI	TUX	UBQ
AFS						1.000 (1.000)			
ARO							1.371 (0.729)		
DOM							1.22 (0.819)		
NoA		1.04 (0.961)							
PER		1.04 (0.961)							
PLE							1.494 (0.669)		
RPI									
TUX			1.607 (0.622)						
UBQ			1.607 (0.622)						

4.4. Supplementary SPSS analysis

In order to provide deeper managerial insights, the means of demographic and behavioural data were compared on SPSS. These included investigation of:

- Any potential association between demographics and repurchase intentions (T-test and one way ANOVA)
- Potential association between demographics and usage location, and between demographics and usage frequency (Cross tabulations and Chi Square test for Independence)
- Non-response bias (Independent sample T-test).

i. Effects of demographics (age, gender and occupation) on consumers' repurchase intentions (RPI).

- *Independent sample T-test was conducted to compare mean RPI scores of male and female respondents.*

Assumptions: Dependent variable RPI was continuous (since mean scores are continuous) and normally distributed, random sampling, observations were independent/ collected in non-group settings. However, Levene's statistic was significant (p < 0.05), therefore equal variances were not assumed (Pallant, 2016).

There was an **insignificant difference between the RPI scores for males** (*M*= 3.360, *SD* = 0.595) **and females** (*M*= 3.290, SD = 0.851); *t* (52.066) = 0.417, *p* = 0.640, confirming males are not significantly more likely to engage in repeat purchases than females.

Table 20: Independent sample T-test comparing RPI means of male and female respondents. p < 0.05 significance level.

RPI *(Equal variances not assumed, p<0.05 Levene's test)*	Male			Female			**T-test for equality of Means**				
	n	***M***	***SD***	***n***	***M***	***SD***	***Mean Difference***	***95% CI***	***df***	***t***	***p (Sig. 2-tailed)***
	25	3.360	0.595	98	3.291	0.852	0.069	-0.225, 0.363	52.066	0.471	**0.640**

- *One way between-groups ANOVA was performed to observe the effects of different age groups on consumers' repurchase intentions.*

Assumptions: Dependent variable RPI was continuous (since mean scores are continuous) and normally distributed, random sampling, observations were independent/ collected in non-group settings. Levene's test was insignificant (*p* = 0.079) confirming homogeneity of variances (Jamieson, 2004; Pallant, 2016).

Overall, results of ANOVA indicate a statistically significant difference at the 95% significance level among the repurchase intentions of different age groups, *F*(2, 125) = 3.739, *p* < 0.05. Post-hoc comparisons using Tukey HSD test reveal that **older millennials aged 30-34** (*M*=3.6700, *SD*= 0.60260) **were significantly more likely to engage in repeat purchases than Gen Zs aged 18 - 24** (*M*=3.1600, *SD*= 0.82648). However, no significant differences were detected between repurchase intentions of Gen Zs and younger Millennials (age 25 -29), and between older and younger millennials.

*Table 21: One way between-groups ANOVA to test the effects of different age groups on RPI. (*p < 0.05 level of significance, 2- tailed).*

				Test of Homogeneity of Variances		**ANOVA**	
Age Groups	***n***	***M***	***SD***	***Levene's Statistic***	***Sig.***	***F (2, 125)***	***Sig. (2-tailed)***
18-24	50	3.1600	0.82648	2.588	0.079	3.739	**0.026***
25-29	53	3.2594	0.79506				
30-34	25	3.6700	0.60260				
Total	128	3.3008	0.79142				
Group Differences							
Age Groups	***Mean Difference***	***Sig. (2-tailed)***	***95% CI***				
(18-24) - (25-29)	-0.09943	0.792	-0.4618	0.2629			
(25-29) - (30-34)	-0.41057	0.078	-0.8565	0.0354			
(18-24) - (30-34)	-.51000*	**0.022***	-0.9602	-0.0598			

- One way between-groups ANOVA for various occupations and repurchase intentions indicates **an insignificant difference among the repurchase intentions of people working in different sectors**, F (6, 121) = 1.873 , p = 0.091.

Table 22: One way between-groups ANOVA to test the effects of different occupations on RPI. (p < 0.05 level of significance, 2-tailed). Note Levene;s Statistic was significant (p = 0.947), confirming homogeneity of

				Test of Homogeneity of Variances		**ANOVA**	
Age Groups	***n***	***M***	***SD***	***Levene's Statistic***	***Sig.***	***F (6, 121)***	***Sig. (2-tailed)***
Student	25	2.9600	0.75925	0.947	0.453	1.873	**0.091**
Public sector-employed	6	3.7083	0.85756				
Private sector-employed	78	3.3814	0.80856				
Self-employed	12	3.0417	0.59193				
House manager/ Family manager	1	4.0000					
Unemployed	4	3.8125	0.51539				
Prefer not to disclose	2	3.3750	0.53033				
Total	128	3.3008	0.79142				

ii. Association between Demographics (age, gender) and App Usage Behaviour (location, frequency) .

- *Chi Square test for Independence was performed using cross tabs to confirm if there was any association between categorial variables age and gender, and app usage frequency and location.*

  Assumptions: Random sampling and independent observations. Yate's continuity correction was used instead of Pearson Chi Square statistic, and Phi instead of Cramer's V, since all analysis were for a 2 X 2 matrix (Pallant, 2016). *p* value was reported using Fisher's Exact test for grids which violated the minimum cell frequency assumption (i.e., at most 20% of cells can have expected count less than 5) (Pallant, 2016).

- App Usage Location (at home vs. outside home) and Gender (male vs. female): Chi Square Test for Independence (with Yate's Continuity Correction and Fisher's Exact Test) indicated an **insignificant association between gender and app usage location**, X^2 (1, 123) = 2.198, p = 0.073, *phi* = 0.093 (See Table 24.).

Table 23: Gender X App Usage Location Crosstabulation.

Gender * Location Crosstabulation

			App usage location		Total
			At Home	Outside Home	
Gender	Male	Count	17	8	25
		% within gender	68.0%	32.0%	100.0%
	Female	Count	82	16	98
		% within gender	83.7%	16.3%	100.0%
Total		Count	99	24	123
		% within gender	80.5%	19.5%	100.0%

Table 24: Chi Square test of Independence for Gender X App Usage Location. (p < 0.05 significance level, 2-tailed).

Gender * Location Chi-Square Tests					
	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	3.116[a]	1	0.078	0.093	0.073
Continuity Correction[b]	**2.198**	1	0.138		
Fisher's Exact Test				0.093	**0.073**
N of Valid Cases	123				
a. 1 cells (25.0%) have expected count less than 5. The minimum expected count is 4.88.					
b. Computed only for a 2x2 table					

- App Usage Location and Age (Gen Zs vs. Millennials): Chi Square Test for Independence (with Yate's Continuity Correction) indicated an **insignificant association between age and app usage location**, X^2 (1, 128) = 2.104, p = 0.147, *phi* = 0.092 (Table 26.).

Table 25: Age X App Usage Location Crosstabulation.

Age * Location Crosstabulation					
			App usage location		Total
			At Home	Outside Home	
Age	Gen Zs	Count	37	13	50
		% within age	74.0%	26.0%	100.0%
	Millennials	Count	67	11	78
		% within age	85.9%	14.1%	100.0%
Total		Count	104	24	128
		% within age	81.3%	18.8%	100.0%

Table 26: Chi Square test of Independence for Age X App Usage Location. (p <0.05 level of significance, 2-tailed).

Age * Location Chi-Square Tests			
	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	2.831[a]	1	0.092
Continuity Correction[b]	**2.104**	1	**0.147**
N of Valid Cases	128		
a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 9.38.			
b. Computed only for a 2x2 table			

- App Usage Frequency (high frequency vs. low frequency) and Gender (male vs. female): Chi Square Test for Independence (with Yate's Continuity Correction) indicated an **insignificant association between gender and app usage frequency**, X^2 (1, 123) = 1.108, p = 0.293, *phi* = 0.116 (Table 28.).

Table 27: Gender X App Usage Frequency Crosstabulation.

Gender * Frequency Crosstabulation					
			App Usage Frequency		
			High Frequency Users	Low Frequency Users	Total
Gender	Male	Count	19	6	25
		% within Gender	76.0%	24.0%	100.0%
	Female	Count	61	37	98
		% within Gender	62.2%	37.8%	100.0%
Total		Count	80	43	123
		% within Gender	65.0%	35.0%	100.0%

Table 28: Chi Square Test of Independence for Gender X App Usage Frequency. (p < 0.05 level of significance, 2-tailed).

Chi-Square Tests			
	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	1.657[a]	1	0.198
Continuity Correction[b]	**1.108**	1	**0.293**
N of Valid Cases	123		
a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 8.74.			
b. Computed only for a 2x2 table			

- App Usage Frequency and Age (Gen Zs vs. Millennials): Chi Square Test for Independence (with Yate's Continuity Correction) indicated an **insignificant association between age and app usage frequency**, X^2 (1, 128) = 0.122, p = 0.726, *phi* = 0.705 (Table 30.).

Table 29: Age (Cohort) X App Usage Frequency Crosstabulation.

Age (Cohort) * Frequency Crosstabulation					
			App Usage Frequency		Total
			High Frequency Users	Low Frequency Users	
Age (Cohort)	Gen Zs	Count	31	19	50
		% within age	62.0%	38.0%	100.0%
	Millennials	Count	52	26	78
		% within age	66.7%	33.3%	100.0%
Total		Count	83	45	128
		% within age	64.8%	35.2%	100.0%

Table 30: Chi Square Test of Independence for Age (Cohort) X App Usage Frequency. (p < 0.05 significance level, 2-tailed).

Age (Cohort) * Frequency Chi-Square Tests			
	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	.291[a]	1	0.590
Continuity Correction[b]	**0.122**	1	**0.726**
N of Valid Cases	128		
a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 17.58.			
b. Computed only for a 2x2 table			

iii. Nonresponse bias

As observed in the study by Hsu and Chen (2018), demographic means of early and late respondents were compared using independent samples t- test, to minimize the likelihood of non-response bias. Results reveal that there were **no significant differences in the means of age (*t*(125.073) = -1.555, *p* = 0.122), gender (*t*(124) = 0.444, *p* = 0.658), and occupation (*t*(126) = 0.729, *p* = 0.468) of early and late respondents, thereby minimizing the chances of nonresponse**. Although gender and occupation were non-ratio variables (unlike age), the use of such parametric tests on non-continuous scores has been justified in extant literature (Jamieson, 2004; Hsu and Chen, 2018).

Table 31: Independent sample T-test confirming no differences observed in the mean scores of age, gender, and occupation between early and late respondents. ($p < 0.05$ significance level, 2-tailed).

	Early Respondents			Late Respondents			**T-test for equality of Means**				
	n	***M***	***SD***	***n***	***M***	***SD***	***Mean Difference***	***95% CI***	***df***	***t***	***p (Sig. 2-tailed)***
Age *(Equal variances not assumed, p=0.047 Levene's test)*	64	1.7031	0.77007	64	1.9063	0.70640	-0.20313	-0.461, 0.055	125.073	-1.555	**0.122**
Gender *(Equal variances assumed, p > 0.05 Levene's test)*	64	1.8594	0.43158	62	1.8226	0.49668	0.03679	-0.127, 0.200	124	0.444	**0.658**
Occupation *(Equal Variances Assumed, p > 0.05)*	64	2.9063	1.34186	64	2.7500	1.06904	0.15625	-0.268, 0.580	126	0.729	**0.468**

4.5. Structural Model

Figure 12. illustrates the final structural model obtained after running the proposed conceptual model on Smart PLS. Blue circles denote the variables used in hypotheses testing. Yellow rectangles represent the items that make up each construct. Paths between the construct denote the vales of path coefficients and T- statics (in bracket). The values reported inside each endogenous variable denote R^2, indicating the amount of variance resulting from the corresponding exogenous constructs. For example, 23.7 % of the variance observed in repurchase intentions results from arousal, dominance, and pleasure. Figure 13. depicts a partially refitted version of the model (excluding effects of age), demonstrating all the significant and insignificant paths at $p < 0.05$ level, two-tailed.

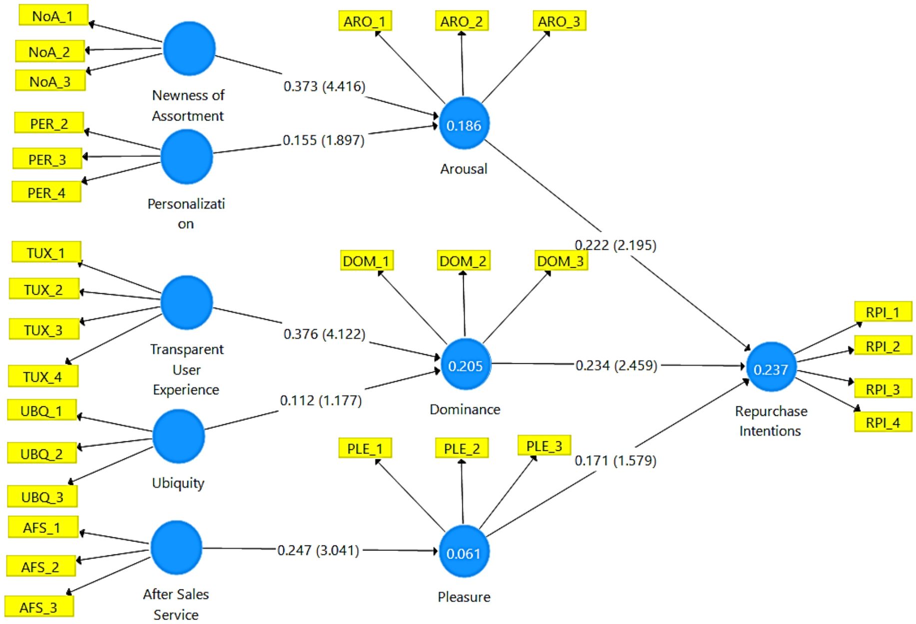

Figure 12: Structural Equation Model Output obtained from Smart PLS 3 for N = 128. All arrows report the path coefficients and t-statistic (in bracket). Path is significant if t-statistic > 1.96. R^2 values are reported inside the blue circles for all endogenous constructs. ($p < 0.05$, 2-tailed).

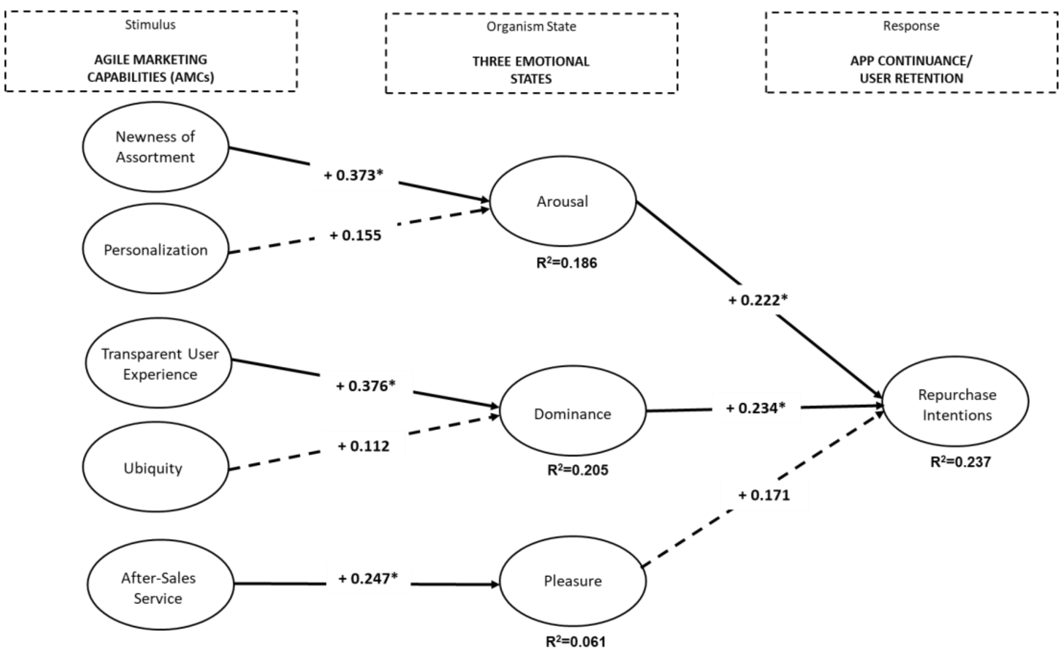

Figure 13: Structural Model depicting the significant paths.
Dashed arrows indicate that the path is insignificant. ($p < 0.05$, 2-tailed), N= 128.*